Variation of household electricity consumption and potential impact of outdoor $PM_{2.5}$ concentration: a comparison between Singapore and Shanghai

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ABSTRACT

The auto-regressive distributed lag (ARDL) bound testing approach was used to study the relationships between the monthly household electricity consumption and outdoor $PM_{2.5}$ concentration with the consideration of ambient temperature and the number of rainy days for Singapore and Shanghai. It is shown that there are significant long-run relationships between the household electricity consumption and the regressors for both Singapore and Shanghai. For Singapore, a 20% increase in the $PM_{2.5}$ concentration of a single month is in the long-run significantly related to a 0.8% increase in the household electricity consumption. This corresponds to an electricity overconsumption of 5.0 GWh, a total of 0.7 – 1.0 million USD in electricity cost, and 2.1 kilotons of CO_2 emission associated with electricity generation. For Shanghai, a 20% decrease in the $PM_{2.5}$ concentration of a single month is in the long-run significantly related to a 2.2% decrease in the household electricity consumption. This corresponds to a 35.0 GWh decrease in the overall household electricity consumption, 1.6 – 5.1 million USD decrease in electricity cost, and 17.5 kilotons of CO_2 emission. The results suggest that the cost of electricity consumption should be included in the economic cost analysis of $PM_{2.5}$ pollution in the future. A 1 ^{o}C increase in the monthly temperature is in the long-run significantly related to a 13.6% increase in the monthly electricity consumption for Singapore, while a 30 degree days increase in heating & cooling days ($HCDD$) is in the long-run significantly related to a 24.9% increase in the monthly electricity consumption for Shanghai. A 5-day increase in the number of rainy days per month is in the long-run significantly related to a 3.0% and 5.8% increase in the monthly electricity consumption for Singapore and Shanghai, respectively.

Keywords: Household electricity consumption; $PM_{2.5}$; ARDL; CO_2 emission; economic cost.

1. INTRODUCTION

It is important to understand the relationships between electricity consumption and its influential factors because it is critical for planning electricity generation capacity and managing electricity supply. Policy makers and investors often rely on these relationships to evaluate the impact of energy conservation and governmental directives on electricity use [1, 2]. Understanding the fluctuations of household electricity consumption also serves an important input for the designing and optimization of new building-related energy plans, such as net zero energy building (NZEB) technologies [3, 4] and home performance with energy star programs [5, 6]. A great number of studies [2, 7-12] have been conducted to study the effects of weather (e.g., temperature and rainy days), and economic factors (e.g., income, electricity tariff, GDP, etc.) on electricity consumption. Some prior studies [2, 8] have explored the relationships between household electricity consumption and various factors for Singapore. For example, the study by Loi and Loo [2] found that the household electricity consumption in Singapore was positively related to temperature and the number of rainy days, and attributed the relationships to the increased use of air-conditioners during hotter periods, and increased use of air-conditioners and time of staying at home during rainy days, respectively. Their study also found that the household electricity consumption was insensitive to tariff and income due to the fact that the electricity bill only accounts for a small portion of the overall household expenditure. On the other hand, relevant information is still limited for Shanghai with one study exploring the influences of temperature only [9].

Little information has been gathered regarding the influences of outdoor $PM_{2.5}$ (particulate matters smaller than 2.5 μm in aerodynamic diameter) concentration towards electricity consumption. Indeed, most of the existing effort has been put to understand how energy-related systems (e.g., power plant, vehicle, and industry) affect outdoor $PM_{2.5}$ concentrations [13, 14] and how $PM_{2.5}$ exposure affects human health [15, 16]. $PM_{2.5}$ poses a great threat to the health of human beings via inhalation exposure, as they have a great potential to penetrate deeply into the human respiratory systems and consist of various chemical constituents such as metal, organic compounds, biological components, sulfate, nitrate, other acidic compounds~~,~~ and surface-adsorbed reactive gases [17]. It has been widely recognized that $PM_{2.5}$ exposure is associated with the increased occurrence of various diseases such as cardiovascular diseases [18, 19], respiratory diseases [20, 21], asthma [22, 23], and lung cancer [24]. Daily mortality data showed that, on a global scale, 4% to 8% of premature deaths may occur due to exposure to suspended PM and especially $PM_{2.5}$ in the environment [25].

During haze episodes that are signified by the spikes of outdoor $PM_{2.5}$ concentration, people are generally advised to stay indoors, close windows and doors, and use air-conditioners and air purifiers (to clean indoor air) [26, 27]. These typical mitigation measures serve to change the style of electricity use and could potentially lead to variation of household electricity consumption. Especially, the prolonged use of air-conditioners could significantly increase household electricity consumption in view of the fact that air-conditioners are widely used in modern megacities in temperate and tropical regions and air-conditioning accounts for a significant proportion of overall household electricity consumption for mechanically ventilated premises [28].

Haze episodes have been one of the severest environmental pollution problems for both Singapore and Shanghai. Singapore suffers from the near-annual spells of haze which is caused by the PM released during uncontrolled forest and peat-land burning activities in Indonesia. The duration, intensity, and impacts of the exogenous haze episodes are largely dependent on prevailing weather conditions (e.g., transboundary wind conditions) and the extent of fires in Indonesia [29]. In Indonesia, current plantation preparation methods still largely rely on land clearing fires, making PM pollution a persistent problem for Singapore, especially during El Niño years. As a developed, tropical country, air-conditioners are commonly used indoors to achieve thermal comfort, but they are one of the most electricity-consuming residential appliances in Singapore [30]. Shanghai experiences frequent, severe haze conditions attributed to various endogenous sources, such as coal power plant combustion, motor vehicle emission, and industrial emission [31, 32]. It is worth noting that more than 60% of electricity comes from coal-fired power plants, which serve as a major PM contributor in China, and it was predicted that the proportion of coal as fuel source for power plant would decrease by 10% only in 2020 [33]. At the same time, vehicle ownership of Shanghai had exceeded 2.2 million by the end of 2014 and is expected to increase at a yearly rate of 10% [34]. Hence, $PM_{2.5}$ pollution is expected to pose a long-term burden to the air quality of Shanghai. In pace with the rapid advancement in economy and living standards, the ownership of air-conditioners in Shanghai reached 207 per hundred households in 2013, while electricity shortage was over 1 million kWh or even higher during some high demand periods [35].

In this work, we conduct econometric analysis to evaluate the association between household electricity consumption and ambient $PM_{2.5}$ concentration for Singapore and Shanghai. The effects of ambient temperature and the number of rainy days are also considered to complete the analysis. The haze conditions of Singapore and Shanghai are different, which allows us to explore the relationships with respect to the $PM_{2.5}$ concentrations of different modes and magnitudes. The implication of $PM_{2.5}$ pollution for economic costs and CO_2 emission are further explored in terms of electricity consumption.

2. METHODOLOGY

The raw data is firstly compiled, followed by the specification of empirical models. Based on the raw data, descriptive analysis could be conducted and includes the illustration of temporal variations of monthly variables and the calculation of descriptive statistics. In the econometric analysis, the stationarity of variables are examined, which will justify the use of the auto-regressive distributed lag (ARDL) bounds testing approach proposed by Pesaran et al. [36]. The ARDL bounds testing approach will involve the determination of long-run relationship and the estimation of long-run and short-run coefficients, respectively. Lastly, the stability of estimated coefficients will be evaluated based on parameter constancy tests. A schematic of the methodology in this work is shown in Figure 1.

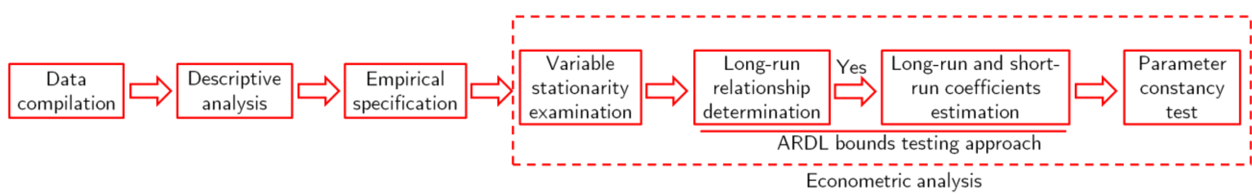


Figure 1. A schematic of methodology.

2.1 Raw data

Singapore has a total population of 5.54 million and a land area of 719.1 km^2 in 2015 [37]. The climate of Singapore is characterized by a northeast monsoon season from December to early March, a southwest monsoon season from June to September, and two interspersed inter-monsoon period otherwise [38]. Generally, the southwest monsoon season is featured by dry and relatively hot weather which would favor the formation of haze episodes. The hourly 24-hr $PM_{2.5}$ mass concentration data of five parts of Singapore (i.e., north, south, east, west, and central corresponding to 12 ambient monitoring stations and 2 road-side stations) from December 2012 to December 2015 was obtained from the website of National Environmental Agency (NEA), Singapore [39]. Since April 1st, 2014, the $PM_{2.5}$ concentration was not reported on its own but subsumed into PSI readings. In this case, the $PM_{2.5}$ concentration data after April 1st, 2014 was back-calculated based on the reported PSI data [40], considering that $PM_{2.5}$ serves as the dominant air pollutant for Singapore, especially during haze episodes [41]. The 24-hr $PM_{2.5}$ mass concentration data for the five parts of Singapore at 8 am, 12 pm, and 4 pm each day was averaged to calculate the average daily $PM_{2.5}$ concentration, and based on which the monthly $PM_{2.5}$ mass concentration was calculated. The monthly household electricity consumption data was obtained from the website of Energy Market Authority (EMA), Singapore [42]. The original electricity consumption data denotes the monthly electricity consumed per household and thus the potential effect of population (household) expansion could be ignored. The original monthly electricity consumption data was normalized by the ratio between the number of days of each month and 30 (days) to remove the potential effect of month length (i.e. the number days in a month). The average monthly temperature and number of rainy days are considered in the econometric analysis. The original data of temperature and the number of rainy days (precipitation > 2.5mm) was obtained from the website of the Department of Statistics (DoS), Singapore [43]. The data of rainy days was normalized by the ratio between the number of days of each month and 30 (days) to remove the potential effect of month length (i.e. the number days in a month). Electricity tariff and income could be potential influential factors for electricity consumption [44, 45]. However, as mentioned earlier, the electricity consumption in Singapore was found to be insensitive to both electricity tariff and income due to the fact that electricity bill only accounts for a small portion of the overall household expenditure [2]. Hence, the electricity tariff and income are not explored further.

Shanghai has a total population of 24.26 million and a land area of 6340.5 km^2 as of 2014 [34]. Shanghai has a humid subtropical climate under the influence of the Asian monsoon and is generally wet and hot during summer while relatively dry and cold during winter. The meteorological conditions during winter favor the formation of haze in Shanghai. The $PM_{2.5}$ concentration data from July 2013 to July 2016 was resourced from the Mission China (MC) air quality monitoring program by the U.S. Department of State [46]. The measurements were taken at a 1-hour interval by a Met One BAM-1020 β attenuation monitor (Met One Instruments, USA) [47] at the rooftop of the U.S. consulate general’s building located in Xuhui district, Shanghai. Although the data source claimed that the data was not fully verified, recent studies [48] showed that the data from the MC air quality monitoring program was in good agreement with their measurements. Furthermore, the utility of the $PM_{2.5}$ data from the MC air quality monitoring program has been demonstrated by the study of San Martini et al. [49]. Recent studies [50, 51] also showed that the $PM_{2.5}$ concentration data from the MC program reflected well the citywide $PM_{2.5}$ data measured at multiple sites. Since this work does not explore the spatial distribution of household electricity consumption in Shanghai, the $PM_{2.5}$ data from the MC air quality monitoring program was used as an overall indicator for $PM_{2.5}$ exposure in Shanghai. The daily $PM_{2.5}$ concentration data was calculated by averaging the hourly-based original data (hours without data records were excluded during the averaging). The data of five days (09/01/2013, 09/02/2013, 10/12/2015, 10/13/2015, and 03/20/2016) is missing and not considered in this work. The monthly data of overall household electricity consumption was obtained from Shanghai Municipal Development and Reform Commission (SHDRC), Shanghai [52]. The original data was divided by the number of households to calculate the electricity consumption per household. However, the data of the number of households is available only up to the year 2014 from Shanghai Statistics Yearbook, 2015 [34]. To estimate the number of households of the year 2015 and 2016, the data during the year 1990-2014 was accumulated and fitted by a linear function ($y = 4.593x + 420.93$, R^2=0.993) with x as the sequence of a year (e.g., 1 corresponds to year 1990 and 26 corresponds to year 2015) and y as the predicted number of households. Similar to the case of Singapore, the household electricity consumption is further normalized by the ratio between the number of days of each month and 30 (days) to remove the potential effect of month length. Unlike Singapore, Shanghai has distinctly hot (summer) and cold (winter) seasons and significant amount of electricity is spent for cooling and heating during summer and winter, respectively. As a result, the relationship between household electricity consumption and ambient temperature is generally non-linear [53, 54]. In this case, two derivative temperature variables, heating degree days ($HDD = \sum_i^n \mathrm{Max}(0, T_{ref} - T_{tmin})$) and cooling degree days ($CDD = \sum_i^n \mathrm{Max}(0, T_{tmax} - T_{ref})$), respectively, were calculated [1, 55]. T_{tmin} and T_{tmax} denote the minimum and maximum temperature on day i of a month. T_{ref} is the reference temperature which is set to be 10 ^{o}C and 25 ^{o}C for HDD and CDD, respectively

[56]. The calculated HDD and CDD were normalized by the ratio between the number of days of each month and 30 (days) to remove the potential effect of month length. Since HDD and CDD are correlated with each other (e.g., large HDD values correspond to small CDD values, and vice versa), it could potentially lead to multicollinearity if they are used in the econometric analysis directly. Hence, a secondary variable, heating & cooling degree days, $HCDD = (HDD + CDD)/2$ that is featured by peaks during both heating and cooling seasons is used in the econometric analysis for Shanghai. Using $HCDD$ instead of separate HDD and CDD also helps to prevent the potential multicollinearity between $PM_{2.5}$ concentration and HDD and CDD. The temperature data was resourced from Weather Underground [57]. The data of the number of rainy days (including snowy days) was also obtained from Weather Underground [57]. Similar to the case of Singapore, the original data of rainy days was normalized by the ratio between the number of days of each month and 30 (days) to remove the potential effect of month length. In Shanghai, the power sector is regulated and the tariff keeps relatively stable during the period considered in this work [58]. Hence, tariff is not considered as a factor. Only yearly average wage data is available from Shanghai Statistics Yearbook, 2015 [34]. Similar to the case of Singapore, it is considered that the electricity bill should only account for a small share in the overall household expenditure and thus the household income is not further considered. The temporal variations and descriptive statistics (e.g., means, standard deviations, skewness, and kurtosis) of the monthly variables are presented in a descriptive analysis.

2.2 Empirical specification

For Singapore, the electricity consumption per household (EC) is specified as a function of $PM_{2.5}$ concentration (PM), temperature (T), and the number of rainy days (RD).

$$\ln EC_t = \alpha_0 + \alpha_1 \ln PM_t + \alpha_2 T_t + \alpha_3 RD_t + \alpha_4 t + \varepsilon_t \quad (1)$$

where ln $[x]$ denotes the natural log of variable x; t denotes the time trend; ε denotes a random error, i.e. a normally and identically distributed white noise. High outdoor $PM_{2.5}$ concentrations may stimulate people to (1) use air-conditioners and/or air purifiers to clean indoor air, (2) increase indoor activities and the use of electrical appliances, and (3) close windows and doors which in turn leads to the increased use of fans and air-conditioners in view of the hot and humid climate in Singapore. As a result, α_1 is expected to be positive. α_2 is expected to be positive because higher temperature will increase the usage of fans and air-conditioners for cooling and water heater (people are more likely to take shower). α_3 is expected to be positive as well because rainy days may increase people's indoor activities as inferred by the study of Loi and Loo [2].

For Shanghai, the electricity consumption per household (EC) is specified as a function of $PM_{2.5}$ concentration (PM), $HCDD$, and the number of rainy days (RD).

$$\ln EC_t = \beta_0 + \beta_1 \ln PM_t + \beta_2 HCDD + \beta_3 RD_t + \beta_4 t + \varepsilon_t \quad (2)$$

β_2 is expected to be positive because high $HCDD$ values during summer and winter correspond to the large cooling and heating demand by using electrical appliances, respectively. Similar to the case of Singapore, β_1 and β_3 are expected to be positive.

2.3 Econometric analysis

2.3.1 Stationarity of variable series

The stationarity of each variable is firstly examined based on Augmented Dickey-Fuller (ADF) unit root tests. The maximum lag lengths applied in the tests were determined to be 9 for both the cases of Singapore and Shanghai using the rule of [59] (i.e. $\text{integer}[12\,(N/100)^{1/4}]$ with the number of observations $N = 37$). The Akaike Information Criterion (AIC) is used to select the optimal lag length. The AIC measures the goodness-of-fit of a statistical model for a given set of data. The test results are shown in Table 1. At the 5% significance level, it is shown that the timer series of $\ln EC$, $\ln PM$, T, and RD are stationary at level ($I(0)$) in the case of Singapore, and the time series of $\ln EC$, $\ln PM$, and $HCDD$ are stationary at level ($I(0)$) in the case of Shanghai. The stationarity of the first difference of variables is further tested and the results show that the nonstationary variable (RD for Shanghai) is stationary at the first difference ($I(1)$). Considering both $I(0)$ and $I(1)$) variables are involved and none of the variables are integrated of order $I(2)$, the =ARDL bounds testing approach proposed by Pesaran et al. [36] is used for the econometric analysis. The advantages of this approach include better statistical properties in its error correction models, suitability for the cases with small samples and endogenous explanatory variables, and ability to prevent spurious cointegrating relations between $I(0)$ and other variables as found in Johansen cointegration methods and Granger causality frameworks [60-62]. Indeed, an increasing number of studies [60, 63, 64] have employed this approach to model electricity consumption.

Table 1. Summary of ADF tests on the stationarity of variables

City	Variable	t-Statistics	First difference	t-Statistics	Order of integration†
Singapore	$\ln EC$	-6.4307***	$\Delta \ln EC$#	-8.4145***	$I(0)$
	$\ln PM$	-4.0358**	$\Delta \ln PM*$	-4.9535***	$I(0)$
	T	-5.0469***	ΔT	-4.5360***	$I(0)$
	RD	-4.4398***	ΔRD	-4.5497***	$I(0)$

Shanghai	$\ln EC$	-3.9423**	$\Delta\ln EC$	-5.0617***	$I(0)$
	$\ln PM$	-4.6816***	$\Delta\ln PM*$	-6.4647***	$I(0)$
	$HCDD$	-4.1770**	ΔHDD	-5.7477***	$I(0)$
	RD	-3.2065	ΔRD	-9.9835***	$I(1)$

† Decision is corresponding to the significance level of 5%.

** denote statistical significance at 5% level.

*** denote statistical significance at 1% level.

Intercept and trend specification: both (intercept and trend) for variable and none for first difference.

2.3.2 ARDL bounds testing approach

There are two major steps for the ARDL bounds testing approach: (1) to determine whether a long-run relationship exists among the variables as listed in Eq. (1) and Eq. (2), and (2) to estimate the coefficients (both long-run and short-run) corresponding to Eq. (1) and (2) once there is a long-run relationship. In economics, the long-run refers to a period of time when all relevant production and cost factors are variables while the short-run refers to a period of time when at least one factor is fixed. Generally, the short-run and long-run correspond to relative conceptual time periods and have no definite time dimension. In the first step, corresponding to the empirical models (Eq. (1) and Eq. (2)), a series of unrestricted error correction models (UECM) were constructed and estimated. Specifically, the models with electricity consumption as the dependent variable (DV) are

$$\Delta\ln EC_t = a_0 + a_1\ln EC_{t-1} + a_2\ln PM_{t-1} + a_3\ln T_{t-1} + a_4 RD_{t-1} + \sum_{i=1}^{p} a_{5i}\Delta\ln EC_{t-i} + \sum_{j=0}^{p} a_{6j}\Delta\ln PM_{t-j} + \sum_{j=0}^{p} a_{7j}\Delta\ln T_{t-j} + \sum_{j=0}^{p} a_{8j}\Delta RD_{t-j} + a_9 t + \varepsilon_t \quad (3)$$

and

$$\Delta \ln EC_t = b_0 + b_1 \ln EC_{t-1} + b_2 \ln PM_{t-1} + b_3 HCDD_{t-1} + b_4 RD_{t-1} + \sum_{i=1}^{p} b_{5i} \Delta \ln EC_{t-i} + \sum_{j=0}^{p} b_{6j} \Delta \ln PM_{t-j} + \sum_{j=0}^{p} b_{7j} \Delta HCDD_{t-j} + \sum_{j=0}^{p} b_{8j} \Delta RD_{t-j} + b_9 t + \varepsilon_t \quad (4)$$

for Singapore and Shanghai, respectively. Δ denotes the first difference operator and p denotes the number of lags. The other variables are as previously defined. Since the sample sizes (37) are relatively small in this work, the maximum number of lags could not be large due to potential problems related to the degree of freedom [65, 66]. Hence, the maximum lag lengths in the UECM models are specified to be 4. The AIC is applied to determine the optimal lag length. The significance *F*-test of the lagged levels of the variables is used to test the null hypothesis of no cointegration among the variables (i.e. $H_0: a_1 = a_2 = a_3 = a_4 = 0$ for Eq. (3) and $H_0: b_1 = b_2 = b_3 = b_4 = 0$ for Eq. (4)), The *F*-statistic has a non-standard asymptotic distribution and two critical value bounds corresponding to the specification of purely $I(1)$ (upper bound) and $I(0)$ (lower bound) variables, respectively [36]. In view of the relatively small sample sizes (37) of the current work, we use the critical values developed by the study of Narayan [67] that are more appropriate for the cases of limited data (30 to 80 observations). If the *F*-statistic is greater than the upper bound of the critical value, the null hypothesis of non-cointegration is rejected and there is a long-run relationship among the variables, while it could not be rejected if the *F*-statistic is less than the lower bound of the critical value. Conclusive inference could not be reached if the *F*-statistic falls in-between the bounds. The ARDL bounds testing analysis was conducted using Eviews (IHS Global Inc.).

2.3.3 Test of parameter constancy

The coefficient stability of the models was tested using the cumulative sum of recursive residuals (CUSUM) and the CUSUM of squares (CUSUM-SQ) tests, respectively, as suggested by Pesaran and Pesaran [65]. The CUSUM and CUSUM-SQ measure variations in a sequential manner, and were compared with specified thresholds to assess the coefficient stability in the respective tests.

3. RESULTS AND DISCUSSION

3.1 Descriptive analysis

The temporal variations of household electricity consumption, $PM_{2.5}$ concentration, temperature, and the number of rainy days for Singapore and Shanghai are shown in Figure 2. To facilitate comparison, the monthly temperature in Figure 2 for Shanghai is the average one. Figure 2 (a) shows that the household electricity consumption of both Singapore and Shanghai present significant fluctuation across a year. The household electricity consumption of Singapore generally has major peaks during June to August followed by some consumption plateaus during September to November. The former may correspond to the relatively high-temperature period of a year (Figure 2 (c)), while the latter is coincident with some $PM_{2.5}$ concentration spike periods (Figure 2 (b)). The household electricity consumption of Shanghai generally peaks during August to September and January to March, which correspond to the cooling and heating needs during the summer and winter months, respectively. The monthly household electricity consumption of Singapore and Shanghai ranges from 400 to 550 kWh and 200 to 500 kWh, respectively. The household electricity consumption of Singapore is generally greater than that of Shanghai with the latter showing greater fluctuation. However, there is an exception for

Shanghai corresponding to August and September 2013 when the electricity consumption shoots up to over 600 kWh. This is coincident with the significantly higher temperature during the months as shown in Figure 2 (c) and thus the cooling demand. Shanghai is experiencing significantly worse $PM_{2.5}$ pollution than Singapore with the $PM_{2.5}$ concentration exceeding the World Health Organization (WHO) annual standard of 35 $\mu g/m^3$ during the most months and the peak monthly levels of around 100 $\mu g/m^3$. Hence, the $PM_{2.5}$ pollution should be a more frequent and common environmental problem for Shanghai. In 2015, Singapore experienced two severe haze months during September and October which should be related to drier-than-normal weather conditions caused by El Niño events. The $PM_{2.5}$ concentration spikes for Singapore present more randomness than those of Shanghai which generally occur during November to January. The patterns of haze episodes are different between Singapore and Shanghai because of differences in PM sources and climate. Figure 2 (c) shows that as a tropical city, the temperature of Singapore is relatively stable and uniform across a year with only a slight increase during June to August, while the temperature of Shanghai presents apparent seasonality. Figure 2 (d) shows that the monthly number of rainy days could range from less than 5 to over 20 days and does not present obvious seasonality for both Singapore and Shanghai.

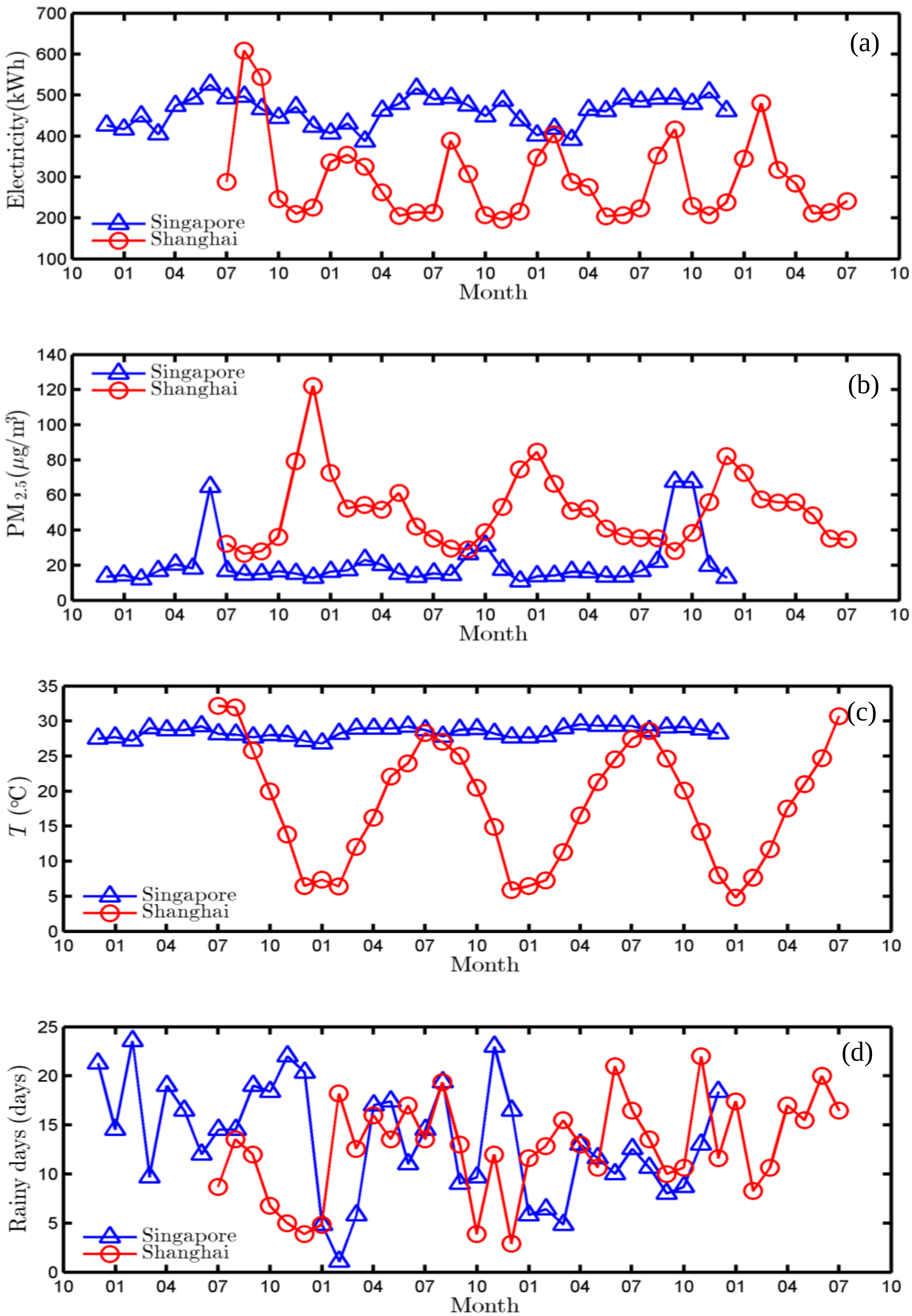


Figure 2. The temporal variation of (a) monthly household electricity consumption, (b) PM2.5 concentration, (c) temperature, and (d) the number of rainy days, for Singapore and Shanghai.

A summary of the descriptive statistics of monthly variables is given in Table 2. To facilitate comparison, the data related to the monthly average temperature is given in Table 2 for Shanghai. It is shown that the average monthly household electricity of Singapore is around 1.6 times that of Shanghai, while Shanghai experiences around 2.5 times greater fluctuation in household electricity consumption than Singapore as denoted by both the standard deviations and the ranges between the minimum and maximum electricity consumption. The average, minimum, and maximum $PM_{2.5}$ concentrations of Shanghai are around 2.5 times those of Singapore, showing that Shanghai experiences much more serious $PM_{2.5}$ pollution than Singapore. The average temperature of Shanghai is around 10 ^{o}C less than that of Singapore, while the temperature standard deviation of Shanghai is about one order of magnitude higher than that of Singapore due to the existing of greater seasonality as shown in Figure 2 (c). The descriptive statistics of the number of rainy days is similar to each other between Singapore and Shanghai. The negative skewness (EC, T, and RD for Singapore while T and RD for Shanghai) means that the smaller, left-tail values dominate the respective distributions. The kurtosis of PM is significantly larger than that of other variables for Singapore, suggesting that the variance of PM is more contributed by infrequent extreme deviations, i.e. occasional haze episodes.

Table 2. Descriptive statistics of monthly variables

City	Variable	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
Singapore	EC (kWh)	460.34	36.56	387.10	525.10	-0.41	2.18
	PM (μg/m^3)	20.68	14.38	10.81	67.61	2.70	8.95
	T (^{o}C)	28.43	0.72	26.80	29.55	-0.42	2.13

	RD (days)	13.44	5.71	1.07	23.57	-0.10	2.19
Shanghai	EC (kWh)	292.94	99.93	195.29	609.06	1.42	4.70
	PM (μg/m^3)	51.01	20.44	26.52	122.15	1.29	5.11
	T (^{o}C)	18.07	8.50	4.81	32.16	-0.05	1.73
	RD (days)	12.73	4.91	2.90	22.00	-0.25	2.49

3.2 ARDL cointegration analysis

The results of *F*-statistics for the cointegration analysis are listed in Table 3 together with the critical value bounds for small samples from the study of Narayan [67]. When the household electricity consumption is the dependent variable, the *F*-statistics is greater than the upper bound critical values at the 1% significance level for both Singapore and Shanghai. Therefore, the null hypothesis of no cointegration is rejected and there is a long-run relationship between household electricity consumption and other regressors (temperature, outdoor $PM_{2.5}$ concentration, and the number of rainy days) for both Singapore and Shanghai. To ensure consistent parameter estimation, the error terms of the ARDL models (Eq. (3) and Eq. (4)) need to be serially independent. We conducted residual-based diagnostic tests, i.e. the Ljung–Box Q-statistic test for the first 16 lags which showed that there is no autocorrelation in the residuals for both the cases of Singapore and Shanghai (results not shown for brevity).

Table 3. Summary of *F*-tests

City	*F*-statistics			
Singapore ($k = 3$)[#]	$F_2(EC \vert PM, T, RD)$ =18.5824***	$F_{PM}(PM \vert EC, T, RD)$ =4.8879	$F_T(T \vert EC, PM, RD)$ =12.8042***	$F_{RD}(RD \vert EC, PM, T)$ =10.3305***
Shanghai	$F_{EC}(EC \vert PM, HCDD,$	$F_{PM}(PM \vert EC, HCDD,,$	$F_{HCDD}(HCDD \vert EC,$	$F_{RD}(RD \vert EC, PM,$

($k=3$)	*RD*) =21.1659***	*RD*) =4.7218	*PM*, *RD*) =3.1649	*HCDD*) =5.2070**	
Critical values[&]					
Significance level=1%		Significance level=5%		Significance level=10%	
Lower bound ($I(0)$)	Upper bound ($I(1)$)	Lower bound ($I(0)$)	Upper bound ($I(1)$)	Lower bound ($I(0)$)	Upper bound ($I(1)$)
5.654	6.926	3.936	4.918	3.290	4.176

k is the number of regressors.

& Critical values are from [67] (unrestricted intercept and restricted trend) with respect to 35 observations.

** denote statistical significance at 5% level.

*** denote statistical significance at 1% level.

In view of the long-run relationships between the household electricity consumption and other variables in the models, the long-run and short-run elasticities are further examined. The corresponding ARDL specifications of the long-run models are

$$\ln EC_t = c_0 + \sum_{i=1}^{m1} c_{1i} \ln EC_{t-i} + \sum_{i=1}^{m2} c_{2i} \ln PM_{t-i} + \sum_{i=1}^{m3} c_{3i} T_{t-i} + \sum_{i=1}^{m4} c_{4i} RD_{t-i} + \mu_t \tag{5}$$

and

$$\ln EC_t = d_0 + \sum_{i=1}^{m1} d_{1i} \ln EC_{t-i} + \sum_{i=1}^{m2} d_{2i} \ln PM_{t-i} + \sum_{i=1}^{m3} d_{3i} HCDD_{t-i} + \sum_{i=1}^{m4} d_{4i} RD_{t-i} + \mu_t \tag{6}$$

for Singapore and Shanghai, respectively. As discussed in section 2.2.2, a maximum of 4 lags was employed in Eqs. (5) and (6) and the optimal lag length is determined by minimizing the AIC. The specifications with the optimal lag length are ARDL(1,1,3,2) and ARDL(3,1,3,4) for Singapore and Shanghai, respectively. The corresponding long- and short-run elasticities are listed in Table 4.

For the case of Singapore, Table 4 shows that the error correction term (ECM_{t-1}) is statistically significant at the level of 1% with a negative sign, confirming that a long-run equilibrium relationship exists between the household electricity consumption and the other variables. The household electricity consumption is quickly adjusted by around 130% towards the equilibrium in the first month after a shock. It is shown in Table 4 that the long-run and short-run $PM_{2.5}$ elasticity of household electricity consumption is 0.0401 and 0.0134, respectively. Only the long-run elasticity is significant at the level of 1%. This may suggest that people will not immediately realize the severity of haze episodes and people's response to haze episodes may be modest during an initial period in Singapore. The sign of elasticity is consistent with our expectation that an increase in $PM_{2.5}$ concentration will lead residents to consume more electricity by using electrical appliances for thermal comfort, PM mitigation, and entertainment indoors. Hence, the haze episodes caused by the $PM_{2.5}$ transported from Indonesia by transboundary winds potentially pose an additional stress on electricity grids in Singapore. A 20% increase in $PM_{2.5}$ concentration is related to a 0.8% or 4.1 kWh increase in the electricity consumption per household for an average monthly electricity consumption per household of 460 kWh (Table 2). Considering a total number of 1.2 million households and an electricity tariff ranging from 0.195 to 0.288 Singapore dollars (SGD) per kWh [68] for the past six years in Singapore, this corresponds to an electricity overconsumption of 5.0 GWh and a total of 1.0 – 1.4 million SGD (or 0.7 – 1.0 million USD for an exchange rate of 0.73) in household electricity cost. It is also worth noting that the overconsumed 5.0 GWh electricity in the case of a severe haze month corresponds to 2.1 kilotons of CO_2 emission associated with electricity generation, considering that an average of 425 tons CO_2 was emitted per GWh electricity generated in Singapore [69]. The 2015 Southeast Asian haze is one of the severest ones in the recent years due to the influence of El Niño events. Singapore experienced frequent haze episodes during September and October and the $PM_{2.5}$ concentrations of these two months are around 68 and 67 $\mu g/m^3$, respectively, which corresponds to an approximate increase of 13.4 – 19.8 million SGD (or 9.8 – 14.4 million USD for an exchange rate of 0.73) in the total cost of electricity consumption and 29.2 kilotons in CO_2 emission, compared to two normal and haze-free months with an average monthly $PM_{2.5}$ concentration of 15 $\mu g/m^3$ and electricity consumption of 460 kWh. Most of the existing studies [70-74] conducted economic cost analysis of PM pollution based on its adverse impact on human health. The studies by Quah [70] showed that the direct cost of illness, loss in earnings and productivity, and total health damage caused by the severe 1997 haze ranged from 1.2 to 1.5 million USD, 1.9 to 2.1 million USD, and 3.8 to 4.5 million USD, respectively, the summation of which is less than the increased cost in electricity bill attributed to haze episodes in the year 2015. Therefore, it would be desirable to include the cost of electricity consumption in the economic cost analysis of $PM_{2.5}$ pollution.

Table 4. Long-run and short-run elasticity of household electricity consumption for Singapore and Shanghai

Singapore	Long-run elasticity (DV[&]: lnEC_t)			Short-run elasticity (DV: ΔlnEC_t)			
	lnPM_t	T_t	RD_t	ΔlnPM_t	ΔT_t	ΔRD_t	ECM_{t-1}
Coefficient	0.0401***	0.1272***	0.0046**	0.0134	0.0405***	0.0060***	-1.3343***
Standard error	0.0122	0.0111	0.0020	0.0125	0.0098	0.0011	0.1273
t-statistics	3.297	11.5073	2.3360	1.0691	4.1354	5.3055	-10.4788

Shanghai	Long-run elasticity (DV: lnEC_t)			Short-run elasticity (DV: ΔlnEC_t)			
	lnPM_t	$HCDD_t$	RD_t	ΔlnPM_t	$\Delta HCDD_t$	ΔRD_t	ECM_{t-1}
Coefficient	0.0981***	0.0074***	0.0112***	0.0856	0.0006	0.0075***	-3.1597***
Standard error	0.0179	0.0005	0.0020	0.0459	0.0004	0.0021	0.2764
t-statistics	5.4638	16.5367	5.5454	1.8623	1.4103	3.6619	-11.4337

& DV denotes dependent variable.

** denote statistical significance at 5% level.

*** denote statistical significance at 1% level.

The long-run and short-run temperature elasticity is 0.1272 and 0.0405, respectively with both of them being significant at the level of 1%. The significance of short-run elasticity suggests that people are sensitive to the variation of temperature and respond immediately upon its change. Indeed, since the ambient temperature is already high, a further increase may lead to quick response of people to turn to cooling-related appliances. The positive elasticity is consistent with our expectation that a temperature increase would lead to enhanced use of various electrical appliances (e.g., air-conditioners and water heaters). Corresponding to the long-run elasticity, a 1 ^{o}C increase in the monthly temperature is related to a 13.6% increase in the monthly electricity consumption per household for Singapore.

The long-run and short-run elasticity for the number of rainy days is 0.0060 and 0.0046, respectively. The positive signs suggest that an increase in the monthly number of rainy days is related to an increase in household electricity consumption, which is consistent with our expectation and the finding of Loi and Loo [2] and should be related to the increased indoor activities and thus electrical appliance use. Corresponding to the long-run elasticity, a 5-day increase in the number of rainy days per month is related to a 3.0% increase in the monthly electricity consumption per household for Singapore. The study by Loi and Loo [2] only found a significant short-run elasticity, while the long-run and short-run elasticity is found to be significant at the levels of 5% and 1%, respectively, in this work. This difference may be related to the fact that yearly data is used in the study by Loi and Loo [2] compared to the monthly data in this work.

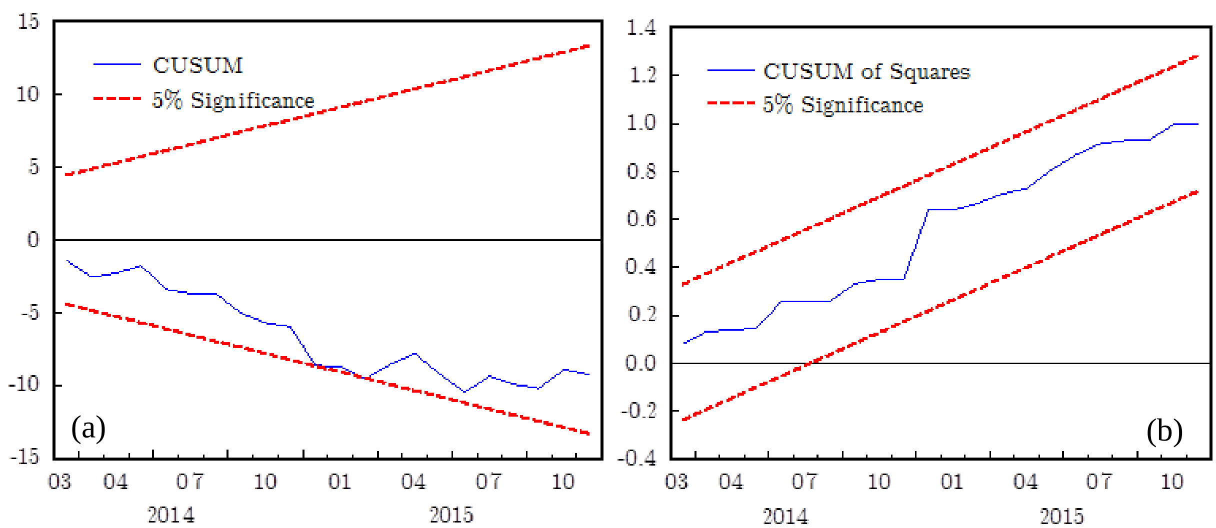
For the case of Shanghai, the error correction term (ECM_{t-1}) is also statistically significant at the level of 1% with a negative sign, confirming that a long-run equilibrium relationship exists between the household electricity consumption and the other variables. The long-run and short-run $PM_{2.5}$ elasticity of household electricity consumption is 0.0981 and 0.0856, respectively. Similar to the case of Singapore, only the long-run elasticity is significant at the level of 1%, which may suggest that people's response to $PM_{2.5}$ concentration variation is not immediate as well. The larger long-run elasticity for the case of Shanghai than Singapore may be related to the fact that Shanghai suffers from significantly severer $PM_{2.5}$ pollution (Figure 2 and Table 2) than Singapore. The $PM_{2.5}$ pollution of Shanghai is endogenous and the $PM_{2.5}$ concentration remains persistently higher than the annual WHO standard across a year. In recent years, various $PM_{2.5}$ mitigation strategies (upgrading of filtration technologies for coal-fired power plants and applying stringent vehicle emission standards) have been proposed and implemented to control the emission of pollutants from primary sources such as coal-fired power plants and vehicle emissions [31]. Corresponding to the long-run elasticity and an average monthly household electricity consumption of 293 kWh (Table 2), a 20% decrease of monthly $PM_{2.5}$ concentration is related to a 2.2% or 6.5 kWh decrease in the household electricity consumption. Shanghai is adopting a tiered and time-of-use electricity pricing system where the electricity tariff is dependent on the amount and time of electricity use. In view of a total of 5.4 million households [34] and an electricity tariff range from 0.307 to 0.977 Chinese Yuan (CNY) [75], the corresponding decreases in the overall household electricity consumption and bill are 35.0 GWh and 10.8 – 34.2 million CNY (or 1.6 – 5.1 million USD for an exchange rate of 0.15), respectively. Specifically, if the monthly average $PM_{2.5}$ concentration is reduced from 100 $\mu g/m^3$ (typical for severe haze months during winters) to 20 $\mu g/m^3$ (annual average level), the yearly saving from electricity consumption could range from 37.4 – 119.0 million USD, which is comparable to the economic cost of health impact due to particulate air pollution in Shanghai as reported by Kan and Chen [76]. Hence, the cost of household electricity overconsumption should be considered in relevant economic analysis in the future. The 35.0 GWh increase in the overall household electricity consumption further corresponds to 17.5 kilotons CO_2 emission if an emission factor of 500 tons per GWh is assumed for electricity generation based on the study by Li et al. [77]. It is worth noting that NZEB plans (such the one based on vehicle to home technologies and renewable electric power sources as proposed by Alirezaei et al. [3]) are receiving increasing attention because they have great potential to reduce energy consumption and CO_2 emission of buildings. In view of the significant relationships between household electricity consumption and $PM_{2.5}$ concentration, it is necessary to consider the outdoor $PM_{2.5}$ concentration as an environmental factor during the deployment and optimization of NZEB plans for haze-hassled cities like Singapore and Shanghai.

The long-run and short-run $HCDD$ elasticity is 0.0074 and 0.0006, respectively. The positive signs suggest that additional household electricity is consumed for the demand of heating and cooling during winter and summer seasons, respectively. Corresponding to the long-run elasticity, a 30 degree days increase in $HCDD$ is related to a 24.9% increase in the monthly electricity consumption per household for Shanghai. The long-run elasticity is significant at the 1% significance level, while the short-run elasticity is not significant. Similar to the case of $PM_{2.5}$, this may suggest that it would take some time for people in Shanghai to respond to temperature change in terms of electricity use, because it may involve the change of living habit.

The long-run and short-run elasticity for the number of rainy days is 0.0112 and 0.0075, respectively, and is significant at the level of 1%. Similar to the case of Singapore, the positive signs mean that the increased number rainy days may correspond to increased indoor activities and thus the use of electrical appliances, which leads to increased electricity consumption. Corresponding to the long-run elasticity, a 5-day increase in the number of rainy days per month is related to a 5.8% increase in the monthly electricity consumption per household for Shanghai This increase in electricity consumption for Shanghai is about 1.9 times of that for Singapore, which may be related to the fact that most of the rainy events in Singapore are thunderstorms and short in duration.

3.3 Parameter constancy

The corresponding graphs of CUMSUM and SUSUM-SQ tests are shown in Figure 3. Since both the CUMSUM and CUSUM-SQ are generally falling within the 5% critical bounds of parameter stability as denoted by the red dash lines, the estimated coefficients of the models are stable at the significance level of 5%.



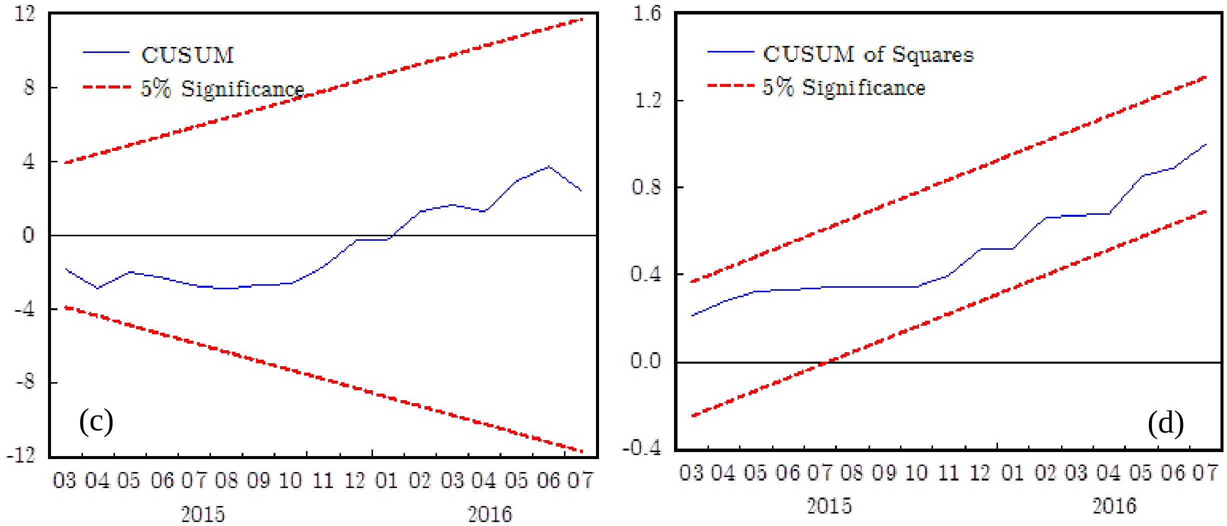


Figure 3. Model stability based on CUSUM and CUSUM-SQ tests for Singapore ((a) and (b)) and Shanghai ((c) and (d)). The red lines denote the critical bounds of parameter stability at the significance level of 5%.

4. CONCLUSIONS

In this work, we used the ARDL bound testing approach to study the relationships between the monthly variation of household electricity consumption and outdoor $PM_{2.5}$ concentration with the consideration of ambient temperature and the number of rainy days for Singapore and Shanghai. There are significant long-run relationships between the household electricity consumption and the regressors for both Singapore and Shanghai. For the case of Singapore, a 20% increase in the $PM_{2.5}$ concentration is significantly related to a 0.8% or 4.1 kWh increase in the electricity consumption per household in the long-run. This corresponds to an electricity overconsumption of 5.0 GWh, a total of 0.7 – 1.0 million USD in household electricity cost, and 2.1 kilotons of CO_2 emission associated with electricity generation. For the case of Shanghai, a 20% decrease in the $PM_{2.5}$ concentration is significantly related to a 2.2% or 6.5 kWh decrease in the household electricity consumption in the long-run. This corresponds to a 35 GWh decrease in the overall household electricity consumption, 1.6 – 5.1 million USD decrease in electricity cost, and 17.5 kilotons of CO_2 emission. This work suggests that the cost of electricity consumption should be included in the economic cost analysis of $PM_{2.5}$ pollution in the future. An increased temperature is significantly related to increased electricity consumption for Singapore due to enhanced cooling demand, while both high and low temperatures are significantly related to the peaks of electricity consumption for Shanghai due to enhanced demand for cooling and heating during the summer and winter seasons, respectively. An increase in the number of rainy days is also found to be significantly related to increased electricity consumption, due to the increased indoor activities and thus the use of electrical appliances.

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